Resource Allocation For The User Centric Mimo-Noma Based IoT Networks

Kingsly.J[1], S. Mohanalakshmi [2]
[1, 2] Dept of ECE
[1, 2] Rohini College of Engineering and Technology

Abstract- *Ultra high reliability and ultra low latency are the key objectives of the internet of things (IoT) with massive connectivity. To support these objectives, we investigate the resource allocation for the user centric multi-cell multiple-input multiple-output non-orthogonal multiple access (MIMO-NOMA) based IoT networks. The macro base station (MBS) equipped with multiple antennas transmits signals to access points (APs) in the backhaul link, and each device can be served by multiple APs in the access link, and the APs serving the same device compose one AP group (APG). The NOMA is applied in each APG to reduce the intra-APG interference. In this paper, the resource allocation problem involving the beam forming optimization and power allocation is formulated as nonconvex optimization problem which is extremely difficult to tackle. In order to reduce the computational complexity, we decompose the resource allocation problem into two subproblems in terms of the beam forming optimization and power allocation. For the beam forming optimization subproblem, the zero-forcing beam forming (ZFBF) algorithm is applied to solve it. When the beam forming strategy is fixed, the power allocation subproblem is still a non convex optimization problem. We first transform it as a difference of two convex functions (DC) problem, and then the DC programming method is adopted to optimize it. Extensive simulation results are presented to demonstrate the effectiveness of the proposed resource allocation scheme for the user-centric MIMO-NOMA IoT networks.*

Keywords*-* Internet of Things (IoT), MIMO, NOMA, power allocation, beam forming.

I. INTRODUCTION

Non-orthogonal multiple access (NOMA) has become an important principle for the design of radio access techniques for the fifth generation (5G) wireless networks. Although several 5G multiple access techniques have been proposed by academia and industry, including power domain NOMA, sparse code multiple access (SCMA) pattern division multiple access (PDMA) low density spreading (LDS) and lattice partition multiple access (LPMA) these techniques are based on the same key concept, where more than one user is served in each orthogonal resource block, e.g., a time slot, a frequency channel, a spreading code, or an orthogonal spatial degree of freedom. Unlike NOMA, conventional orthogonal multiple access (OMA) techniques, such as time division multiple access (TDMA) and orthogonal frequency division multiple access (OFDMA), serve a single user in each orthogonal resource block.

Nevertheless, the principle of NOMA, i.e., removing orthogonality, has not been used in the previous generations of cellular networks. In this content, we note that the philosophy behind 3 NOMA is rarther different from that behind code division multiple access (CDMA). In fact, CDMA is primarily built upon the idea that users are separated by exploiting the differences among their spreading codes, whereas NOMA encourages multiple users to employ exactly the same code. As a consequence, for CDMA, the chip rate has to be much higher than the supported information data rate, e.g., supporting a data rate of 10 Gbps may require a chip rate of a few hundred Gbps, which is difficult to realize with practical hardware. Conventionally, NOMA can be integrated in existing and future wireless systems because of its compatibility with other communication technologies.

The enormous increase in the demand for wireless-related applications has resulted in the conceptualization of the fifth generation (5G) communication systems, where the set of main goals to meet are enhanced spectral efficiency with minimum energy consumption, reduced delay and seamless connectivity. Towards this end, the cognitive radio (CR) technology, which is a way of realizing communication in an opportunistic way, has been viewed as an integral component in the 5G communication systems. A CR examines the activity of a licensed user (also called the primary user) in its dedicated bandwidth through the spectrum sensing (SS) technique, whose outcome favors either of the signal present or absent hypotheses. Depending on the knowledge of the statistics of the noise process, the primary signal and fading, several SS methods have been proposed in the literature and their advantages and disadvantages have been discussed. When the exact statistics of all the above mentioned variables are known, the likelihood ratio test is known to be optimal.

When the primary signal is known and the noise is Gaussian, the matched filter (or the replica correlator) is known to maximize the signal-to-noise ratio (SNR). Among the computationally simpler techniques which are blind to the primary signal statistics, energy detection (ED) is simple to implement. When multiple antennas are available on the CR node, several techniques have been reported for SS in the literature. The blindly combined energy detector (BCED) offers a performance similar to that of the conventional ED, when the received samples are independent and identically distributed. However, while the conventional ED is blind to the primary statistics and requires the knowledge of the noise variance, the BCED is blind to both quantities. Moreover, in the practically significant case where the received primary signal samples are correlated due to block fading, BCED outperforms ED. Another technique called as the space-frequency cross product sensing (SFCPS) is also proposed for sensing with multiple CR antennas. However, the analysis of SFCPS is restricted to two antennas, and the complexity of the algorithm significantly increases with an increase in the number of antennas.

On the other hand, the aforementioned requirements for 5G systems, namely the spectral efficiency and massive connectivity can be mitigated through the non-orthogonal multiple access (NOMA) technique. In NOMA, each user is allowed to occupy the entire bandwidth at the same time, and are served by different power levels. The features of downlink NOMA include the superposition coding at the transmitter, and successive interference cancellation (SIC) at the receiver. The power levels for each user are fixed based on their channel strengths, which depends on the distance between each user and the base station (BS). For the users which are far away from the BS – that is, for those users with low channel gains, higher power is allotted. The BS transmits a signal superimposing the signals intended to all the users. At the user end, the user with the highest power allotted decodes its own signal by treating the interference from other users as noise, while the other users carry out SIC. That is, the remaining users first decode the signals which have been assigned higher power, before decoding their own signal. Recently, the performance of multiple-input multiple-output (MIMO) NOMA systems have been studied and is shown to outperform MIMO-based orthogonal multiple access (OMA) technique, in terms of spectral efficiency. In a typical CR network, multiple access techniques such as time division multiple access (TDMA) and frequency division multiple access (FDMA) are used to accommodate multiple CR users in the sensed-to-be available spectrum.

II. LITERATURE SURVEY

In this paper, propose a novel and effective deep learning (DL)-aided NOMA system, in which several NOMA users with random deployment are served by one base station (BS). Since DL is advantageous in that it allows training the input signals and detecting sharply changing channel conditions, we exploit it to address wireless NOMA channels in an end-to-end manner. Specifically, it is employed in the proposed NOMA system to learn a completely unknown channel environment. A long short-term memory (LSTM) network based on DL is incorporated into a typical NOMA system, enabling the proposed scheme to detect the channel characteristics automatically. In the proposed strategy, the LSTM is first trained by simulated data under different channel conditions via offline learning, and then the corresponding output data can be obtained based on the current input data used during the online learning process. In general, we build, train and test the proposed cooperative framework to realize automatic encoding, decoding and channel detection in an additive white Gaussian noise (AWGN) channel.

This work advocates the use of deep learning to perform max-min and max-prod power allocation in the downlink of Massive MIMO networks. More precisely, a deep neural network is trained to learn the map between the positions of user equipments (UEs) and the optimal power allocation policies, and then used to predict the power allocation profiles for a new set of UEs' positions. The use of deep learning significantly improves the complexity-performance trade-off of power allocation, compared to traditional optimization-oriented methods. Particularly, the proposed approach does not require the computation of any statistical average, which would be instead necessary by using standard methods, and is able to guarantee near-optimal performance.

Non-Orthogonal Multiple Access (NOMA) has recently been considered as a key enabling technique for 5G cellular systems. In NOMA, by exploiting the channel gain differences, multiple users are multiplexed into transmission power domain and then non-orthogonally scheduled for transmission on the same spectrum resources. Successive interference cancellation (SIC) is then applied at the receiver(s) to decode the message signals. In this paper, first briefly describe the differences in the working principles of uplink and downlink NOMA transmissions in a cellular wireless system. Then, for both uplink and downlink NOMA, formulate a sum-throughput maximization problem in a cell such that the user clustering (i.e., grouping users into a single cluster or multiple clusters) and power allocations in NOMA cluster(s) can be optimized under transmission power constraints, minimum rate requirements of the users, and SIC constraints. Due to the combinatorial nature of the formulated mixed integer non-linear programming (MINLP) problem, we solve the problem in two steps, i.e., by first grouping users into clusters and then optimizing their respective power allocations. In particular, propose a low-complexity sub-optimal user grouping scheme. The proposed scheme exploits the channel gain differences among users in a NOMA cluster and groups them into a single cluster or multiple clusters in order to enhance the sumthroughput of the system. For a given set of NOMA clusters, we then derive the optimal power allocation policy that maximizes the sum-throughput per NOMA cluster and in turn maximizes the overall system throughput. Using KKT optimality conditions, closed-form solutions for optimal power allocations are derived for any cluster size, considering both uplink and downlink NOMA systems. Numerical results compare the performances of NOMA and orthogonal multiple access (OMA) and illustrate the significance of NOMA in various network scenarios.

Millimeter wave (mmWave) MIMO will likely use hybrid analog and digital precoding, which uses a small number of RF chains to reduce the energy consumption associated with mixed signal components like analog-to-digital components not to mention baseband processing complexity. However, most hybrid precoding techniques consider a fully-connected architecture requiring a large number of phase shifters, which is also energyintensive. In this paper, focus on the more energy-efficient hybrid precoding with sub-connected architecture, and propose a successive interference cancelation (SIC)-based hybrid precoding with near-optimal performance and low complexity. Inspired by the idea of SIC for multi-user signal detection, we first propose to decompose the total achievable rate optimization problem with non-convex constraints into a series of simple sub-rate optimization problems, each of which only considers one subantenna array. Then, we prove that maximizing the achievable sub-rate of each sub-antenna array is equivalent to simply seeking a precoding vector sufficiently close (in terms of Euclidean distance) to the unconstrained optimal solution. Finally, propose a low-complexity algorithm to realize SIC-based hybrid precoding, which can avoid the need for the singular value decomposition (SVD) and matrix inversion. Complexity evaluation shows that the complexity of SIC-based hybrid precoding is only about 10% as complex as that of the recently proposed spatially sparse precoding in typical mmWave MIMO systems. Simulation results verify that SIC-based hybrid precoding is near-optimal and enjoys higher energy efficiency than the spatially sparse precoding and the fully digital precoding.

III. PROPOSED SYSTEM

In this project investigate the joint resource allocation problem involving the beamforming optimization and power allocation for the user-centric MIMO-NOMA IoT networks in order to maximize the system throughput. Consider both the backhaul downlink (from the MBS to APs) and access downlink (from APs to devices) since the transmission rate of the access downlink is limited by the backhaul downlink. In the backhaul downlink, the MBS equipped with multiple antennas transmits signals to the single-antenna APs. The APs are grouped to serve devices, and the APs in the same AP group (APG) will share the same beamforming vector.

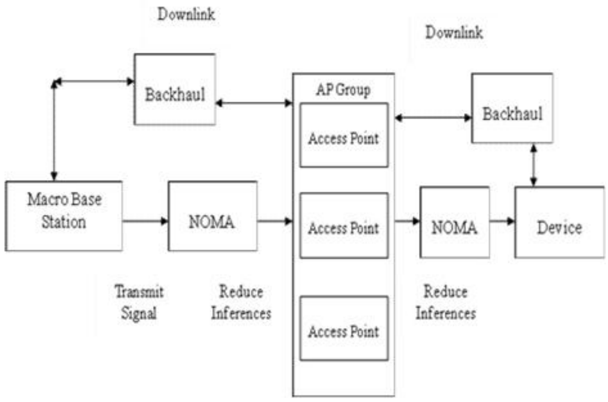


Fig 1.1 Block Diagram

That is, the MBS and each APG form a virtual MIMO system. In the access downlink, each terminal is served by multiple APs simultaneously to enhance the reliability and decrease the latency. In order to decrease the interference, the NOMA is applied both at the AP side and device side for the backhaul downlink and access downlink, respectively. The co-channel interference will be reduced by the SIC. The joint resource allocation involving the beamforming optimization and power allocation is formulated as a nonconvex optimization problem which is extremely difficult to tackle. For the beamforming optimization subproblem, a novel zero-forcing beamforming (ZFBF) algorithm is applied to solve it.

Downlink Signals Model

In this subsection, we provide the signal model of the backhaul downlink model and access downlink respectively for the user-centric MIMO-NOMA IoT.

Backhaul Downlink Signal Model

As a forementioned, the MBS equipped with Nt antennas,and there are M single-antenna APs which are divided into N APGs. It is assumed that the number of APs in the nth APG is M_n, n=1,...,N. Obviously, N P n=1 Mn = M. Then, for the backhaul downlink, Mn APs in the nth APG shares the same beamformer, n=1,...,N, and N independent data streams can be given as

$$X=[x_1,x_2,...,x_N]^T \quad (1)$$

In each APG, the NOMA is applied to reduce the interference caused by the beamformer sharing. In accordance with the principle of NOMA, the AP with better channel condition can decode the signals of the APs with weaker channel condition and then proceeds to subtract it from the received signal and decode its own data.

Access Downlink Signals Model

In this subsection, we give the signal model of the access downlink model of the user-centric MIMO-NOMA IoT networks. For the access downlink, there exists intra-APG interference as a result that multiple APs in the same APG transmit signals to the corresponding device simultaneously. For simplification, it is assumed that the inter-APG interference can be avoided due to the proper APs grouping and resource allocation.

$$y_n = \sum_{m_n=1}^{N_T} h_{m_n}\sqrt{p_{m_n} s_{m_n}} + z_{m_n} \quad (2)$$

where h_{m_n} denotes the channel coefficient from the m_nth AP in the nth APG to the nth device; pmnn represents the transmit power of the m_nth AP in the nth APG to the nth device; zmnn means the AWGN with zero mean and variance δ 2 for the nth device from the mnth AP in the nth APG. Without loss of generality, it is assumed that the channel coefficients can be ordered as:

$$h_{1_n} \geq h_{2_n} \geq \cdots \geq z_{m_n} n \quad (3)$$

According to the principle of NOMA, device n with SIC can successfully decode the signals of the APs with weaker channel condition. That is, the signal of the AP with best channel condition can be first decoded, however, it should experience interference from the other APs in the APG since the device cannot remove the signals from the other APs.

Non-Orthogonal Multiple Access (Noma) Technology

Non-orthogonal multiple access (NOMA) technology has aroused a great concern in terms of enhancing spectrum efficiency. It allows multiple users allocated the same frequency block simultaneously. Users in the same resource block implement multiple access in the power domain through different power levels. At the transmitter NOMA actively introduces interference information. At the receiver, a user with a higher channel gain will be decoded first by using successive interference cancellation (SIC) technology, and the interference from co-subchannel users with lower channel gain can be eliminated directly. NOMA can significantly improve spectral efficiency compared with orthogonal multiple access technology.

We consider a cellular downlink NOMA transmission sys- tem in which the BS transmits the signals to a set of users denoted by $M = \{1,2,\ldots.M\}$. Both the BS and all users are equipped with the single antenna. The channel gain from the BS to the m-th user is. Without loss of generality, the users are assumed to be sorted such that $|h_M| \geq |h_2| \geq \cdots \geq |h_2|$. NOMA enables BS transmit signals on the same channel and serves multiple users simultaneously by using superposition coding techniques.

The global optimal solution due to the non-convexity and NP-hard of the optimization problem. So we divide it into two processes so as to solve the problem more effectively. First, assuming that each subchannel is allocated equal power, we do a user-subchannel matching scheme by introducing equivalent channel gain. Then, based on the subchannels scheme that have been effectively matched, we focus our attention on power allocation and use the backward induction method to find the Stackleberg equilibrium point.

NOMA system, we should use the corresponding reward function in the utility function to represent the cache revenue earned by the system. Based on the above model, it is easy to observe that the SRRH utility function contains three parts: its own energy efficiency income, the interference payment to the reward revenue caused by the caching strategy. Hence, the utility of the MIMO-NOMA can be written as

$$U_n^S = \left(\lambda E_n^S - \sum_{k=1}^{k_S}\sum_{m_k=1}^{M_k}\left|h_{k,m_{k,n}}^{S,M}\right|^2 \sum_{n_k=1}^{N_k} p_{k,n_{k,n}}^S\right) RC_n \quad (4)$$

In the NOMA system, SIC technology is applied at the receivers to eliminate interference which is from other users on the same subchannel. For single cell network, with the channel response normalized by noise (CRNN) H k;i;n, jh, the decoding order of users decreases gradually. This means that users with higher subchannel gains can be decoupled preferentially from the subchannel and eliminate interference from other users with lower subchannel gains. Therefore, we presume that N users are assigned to kth subchannel. The CRNNs are ranked as

$$|H_{1,k}| \geq |H_{2,k}| \geq \cdots \geq |H_{nk,k}| \geq \cdots \geq |H_{Nk,k}|$$

However, in the two-tier NOMA, the total interference also includes the cross-tier interference except the interference which is generated by other users on the same subchannel. The interference is the main limiting factor for SINR. Therefore, we can get the following theorem to decide the user's decoding order. If the SINR received by user i from user j is not less than the user receiving SINR from himself, the user i can be successfully decoded by SIC.

ZERO OPTIMIZATION ALGORITHM

This algorithm includes two parts of the initialization process and matching process. In the initialization part, the user and subchannel preference lists are initialized according to the ECG, and the subchannel matching list SCmatch and unmatched user list UEunmatch are initialized to record the user information matched and unmatched by the subchannel SCn, respectively. In the matching part, when the matching process is not completed, each user selects a subchannel under its own preference list PL UE(m) sorted in descending order of equivalent channel gain and makes an access request. After receiving the request, the corresponding subchannel analyzes its own matching status.

If the number of users allocated on this subchannel is under the maximum value, the user is accessed and the subchannel matching list SCmatch is updated, and the user is deleted from the unmatched user list UEunmatch to represent that the user has matched. If the number of subchannel matching users reaches saturation, then the subchannel will compare the existing users with the requesting user, and according to the subchannel preference list, the optimal combination is selected. The results are updated on the subchannel matching list and unmatched user list. At the same time, removing this subchannel from the preference list of rejected users. When all users are matched, the loop ends. When all users are allocated, if there are still some remaining subchannels at the end, then select the best two users to match according to the subchannel preference list. It is easy to conclude that the complexity of the USMECG algorithm is $O(M * N)$ in the worst case, where M represents the total number of users, and N is the number of subchannels.

IV. SCREEN SHOTS

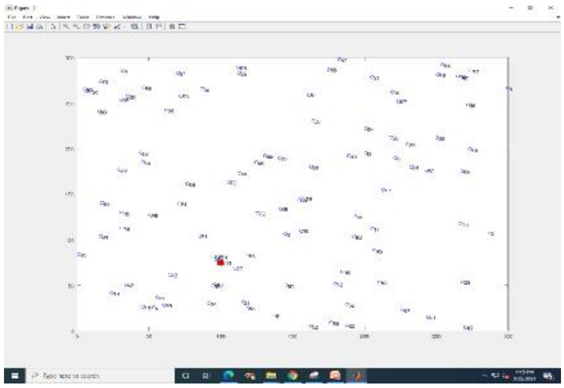


Fig 1.2 Node Creation

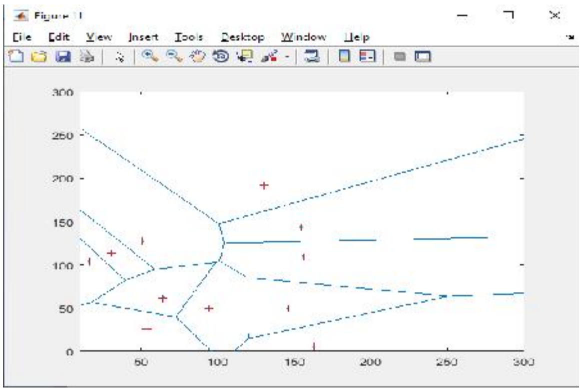


Fig 1.3 Model of AP and Device

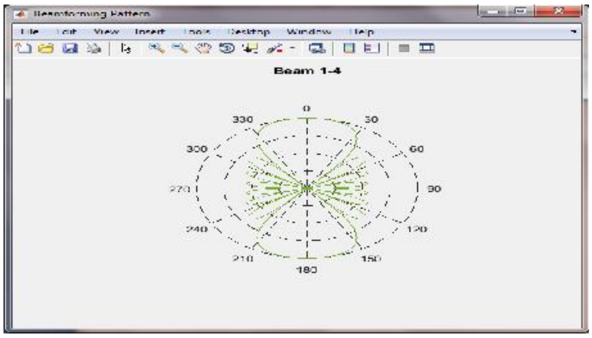


Fig 1.4 Beam forming in the first cluster

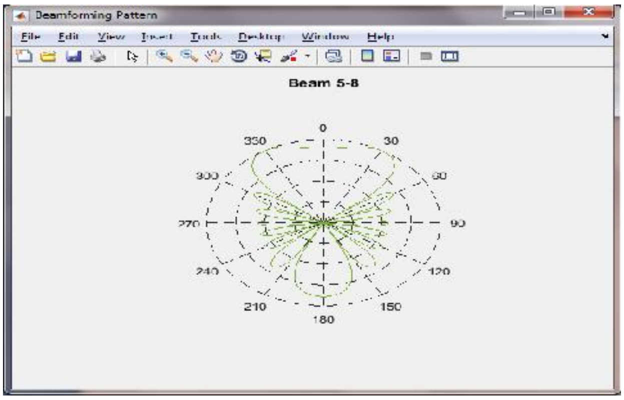


Fig 1.5 Beam forming in the second cluster

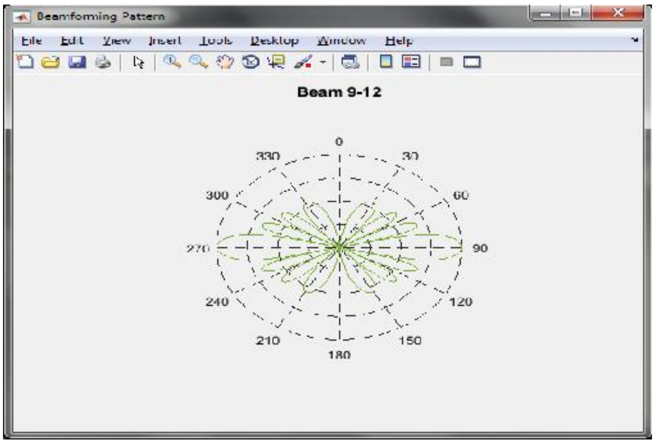


Fig 1.6 Beam forming in the third cluster

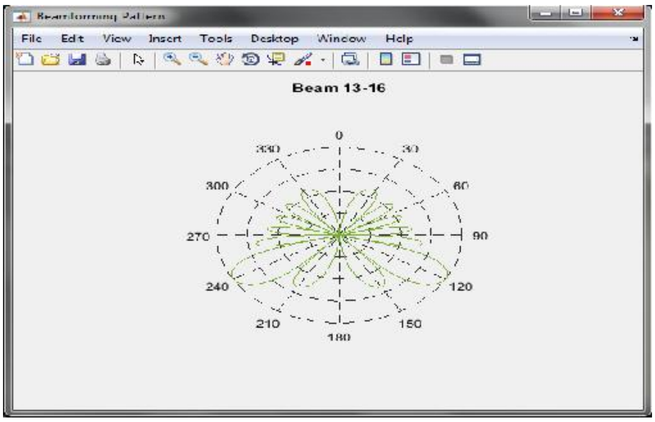
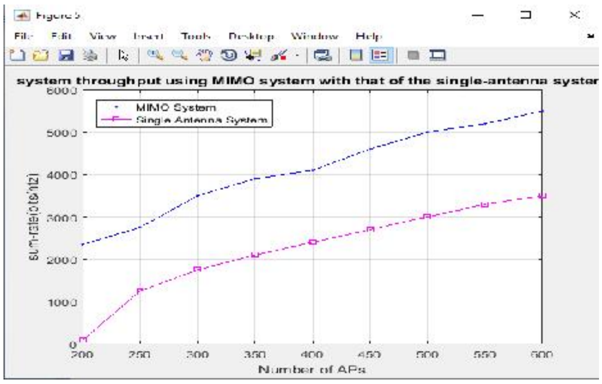


Fig 1.7 Beam forming in the fourth cluster



System Throughput Using MIMO System with Single-Antenna System

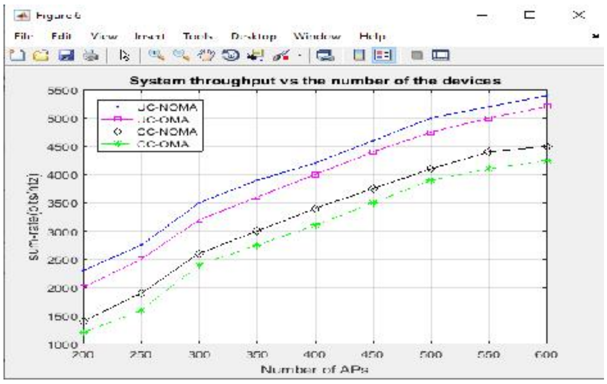


Fig 1.8 System Throughput vs number of Device

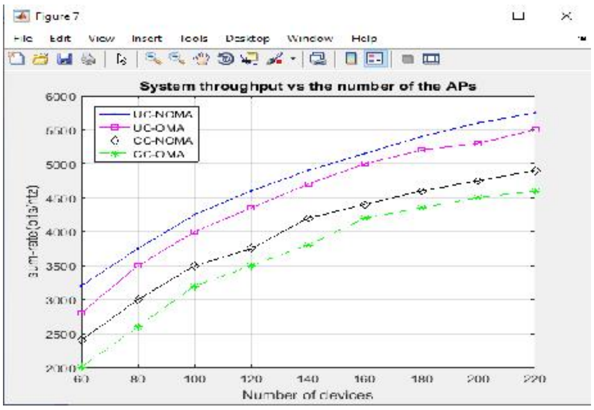


Fig 1.9 System Throughput Vs Number of AP

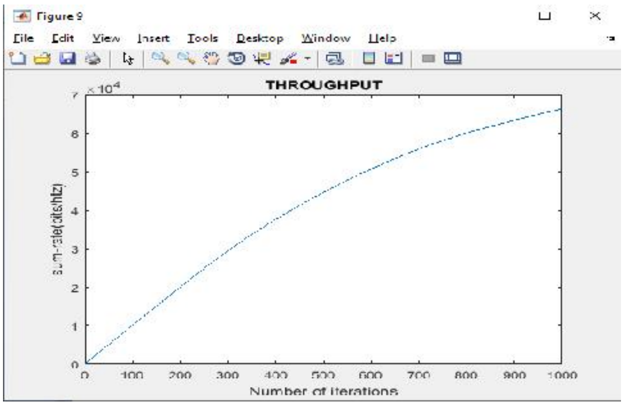


Fig 1.10 Throughput

V. CONCLUSION

In this work have investigated the user-centric access framework for the IoT to enhance the system performance, in which each device are served by multiple APs simultaneously. In order to further improve the spectrum efficiency, the MIMO and NOMA are integrated due to the complementarity of these two issues. Then, the resource allocation involving the beamforming strategy optimization and the power allocation for the user-centric MIMO-NOMA IoT has been investigated, and we have formulated the resource allocation problem as a nonconvex optimization problem which is extremely difficult to tackle. To reduce the computational complexity, decompose the original optimization problem into two optimization subproblems in terms of the beamforming stragegy optimization and power allocation. For the beamforming strategy optimization subproblem, a novel ZFBF algorithm is applied to solve it.

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